THE ERA OF DATA RICH HYDROLOGY

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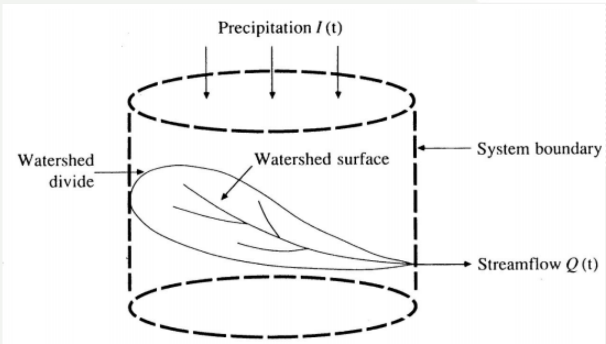
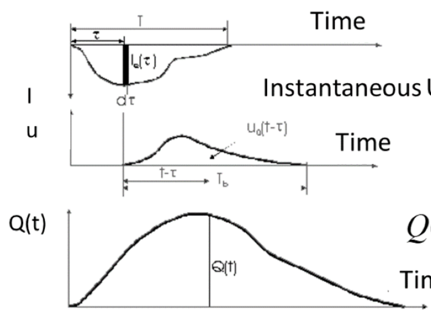
ARDESHIR EBTEHAJ, UNIVERSITY OF MINNESOTA

OCTOBER, 2018

ADVANCES IN HYDROLOGICAL MODELING



Watershed as Hydrological system (Chow et al 1998)



Instantaneous Unit Hydrograph (IUH)

$$Q(t) = \int_0^t I_e(\tau).u(t-\tau)d\tau$$

Physical interpretation of catchment response

1960s

Interconnected conceptual elements

Sacramento
HBV
Xinanjiang
HySIM
NAM
TANK
ARNO GR4J
SWM

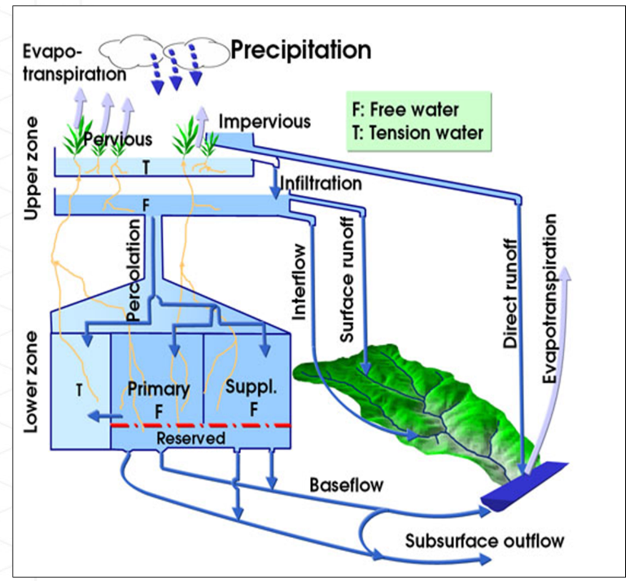
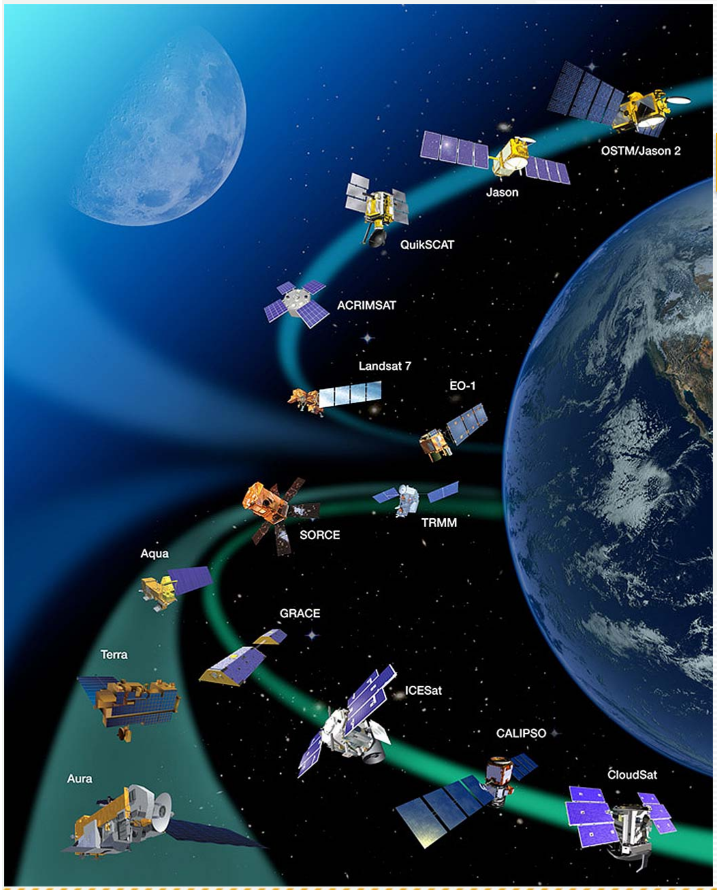


Image: mrcc.isws.illinois.edu

Geomorphological UH; Nonlinear UH; Regionalization of UH

BIG DATA APPROACH IN HYDROLOGY

Georgia Tech

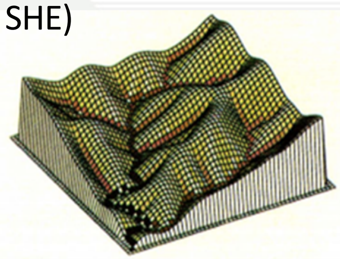


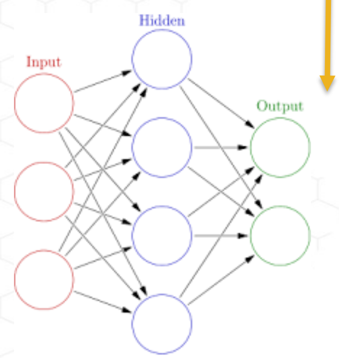
AVHRR/MODIS/Landsat

TRMM, SMOS, GPM, SMAP

Evolution of Big Data Approaches in Hydrology

Spatially Distributed Physically based models (e.g., tRIBS, MIKE SHE)

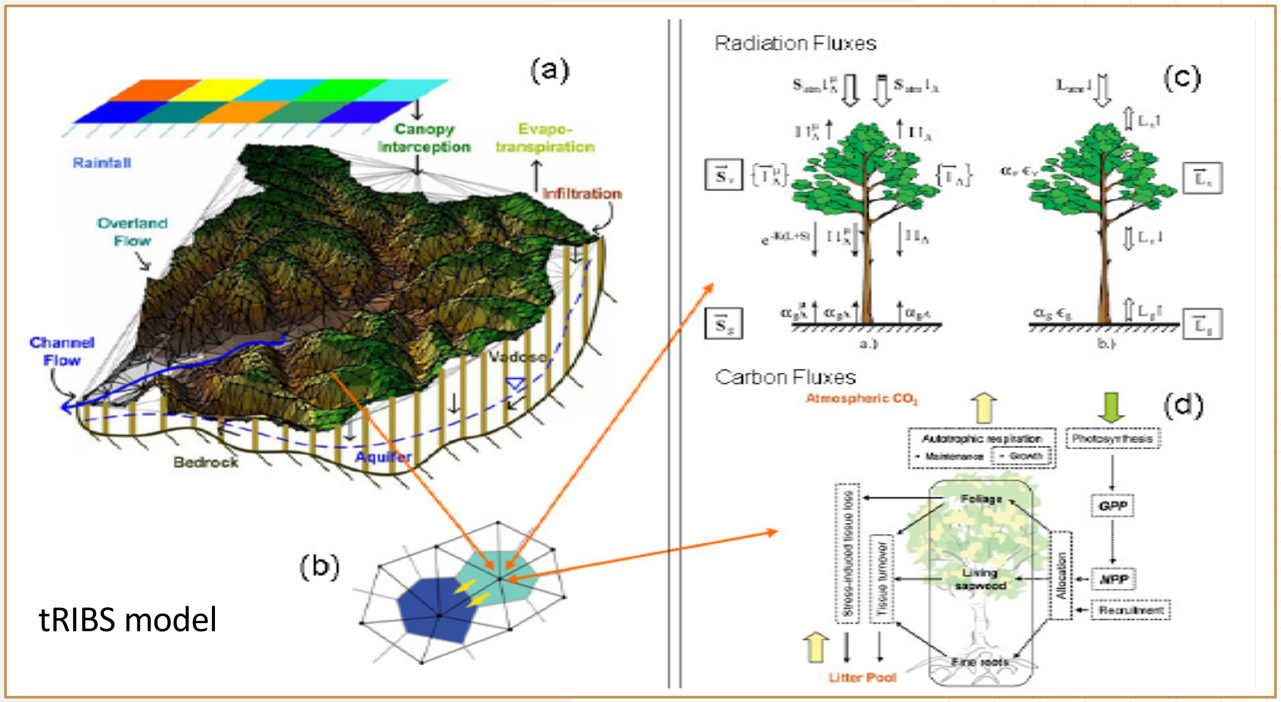




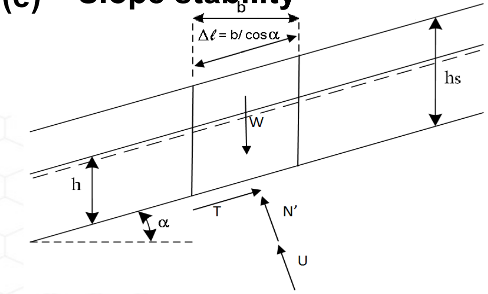
Machine/Deep Learning (retrievals, super resolution)

Data Assimilation: Reliable estimation parameter estimation and state variables

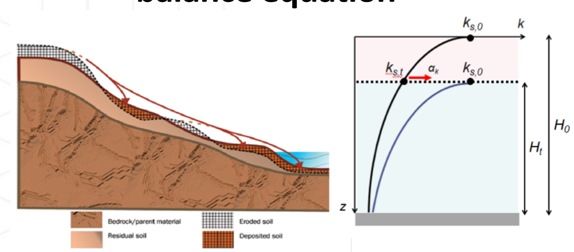
Hybrid Analytics (Combining machine learning with physically based models)



(e) Slope stability



(f) Soil Organic carbon mass balance equation



(g) Soil carbon and nitrogen cycle

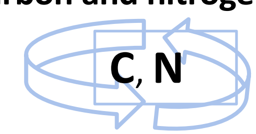
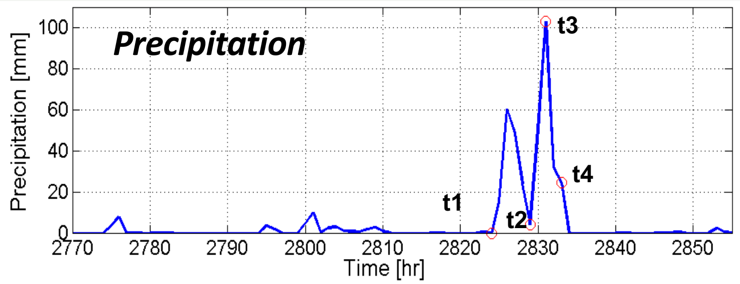
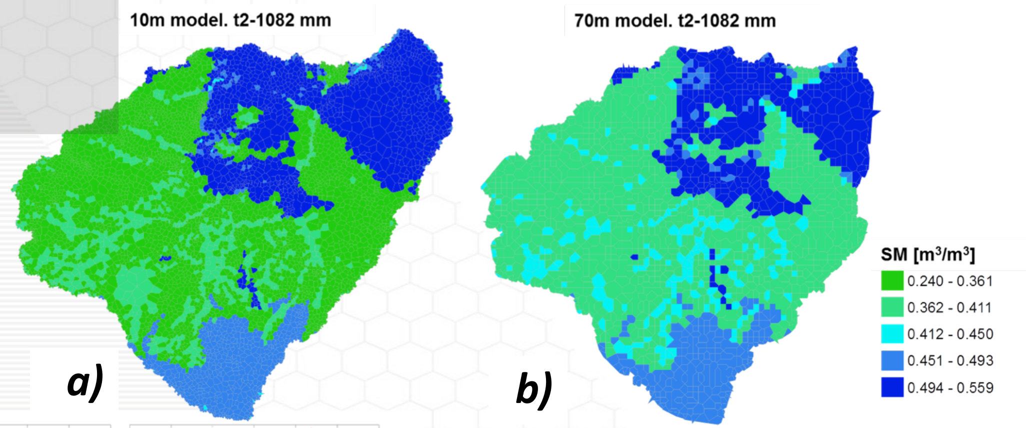


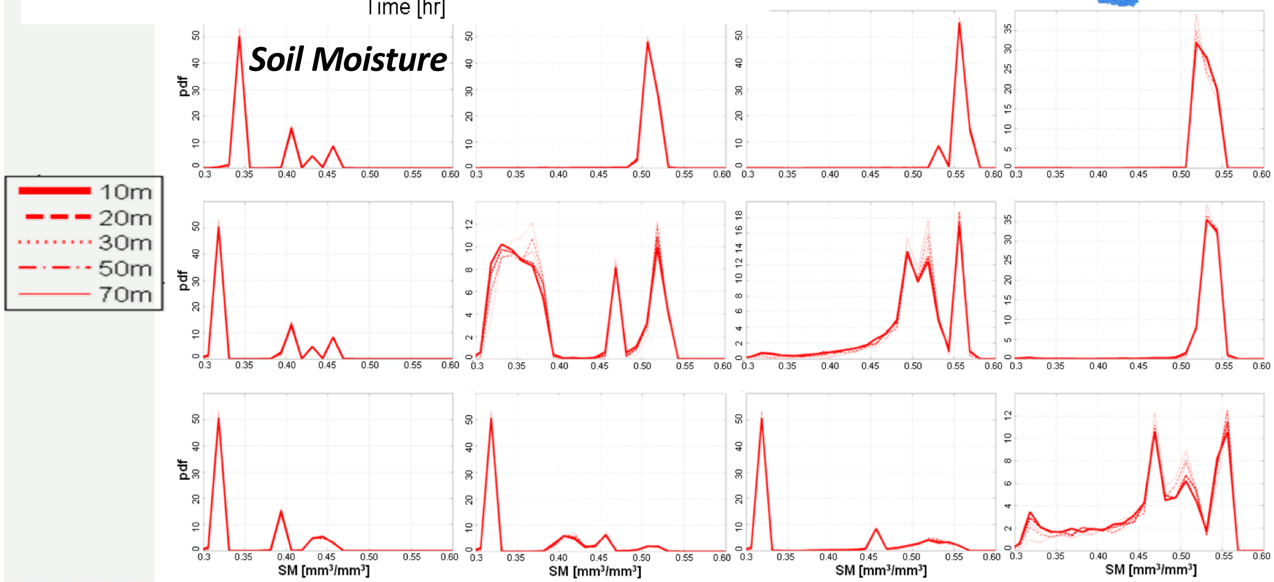
Figure The coupled tRIBS (a-c) and plant physiology model, VEGGIE, (d) is the eco-hydrological framework with additional modules (e) Slope stability sub model, (f) SOC mass balance sub model, (g) Carbon Nitrogen cycle (Lepore et al., 2013)

IMPACT OF DEM RESOLUTION ON SIMULATED SOIL MOISTURE



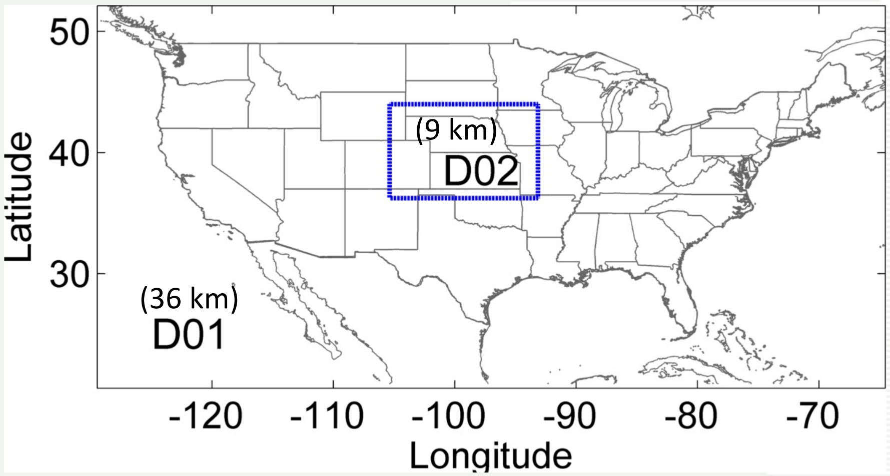


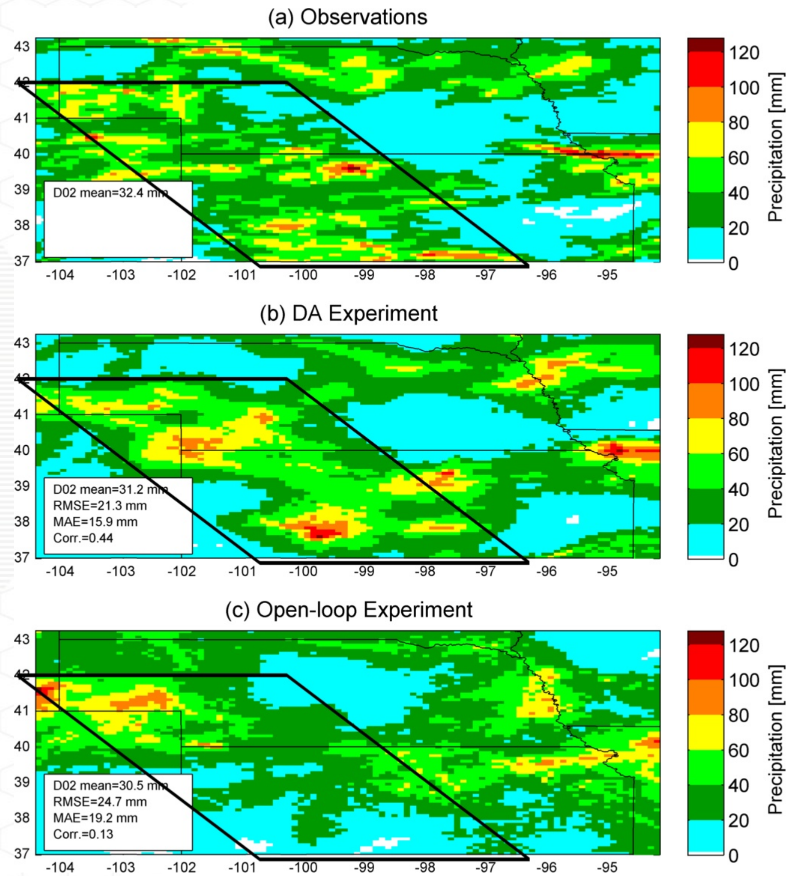
Simulated SM at t2-1082mm for (a)10m DEM and (b) 70m DEM



SM probability density functions at four time steps and three depths for the five resolutions. Differences are pronounced at t2-500mm, t3-1082mm, t4-1512mm.

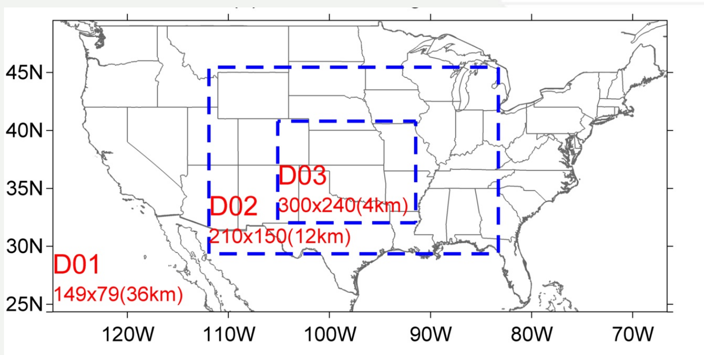
BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION

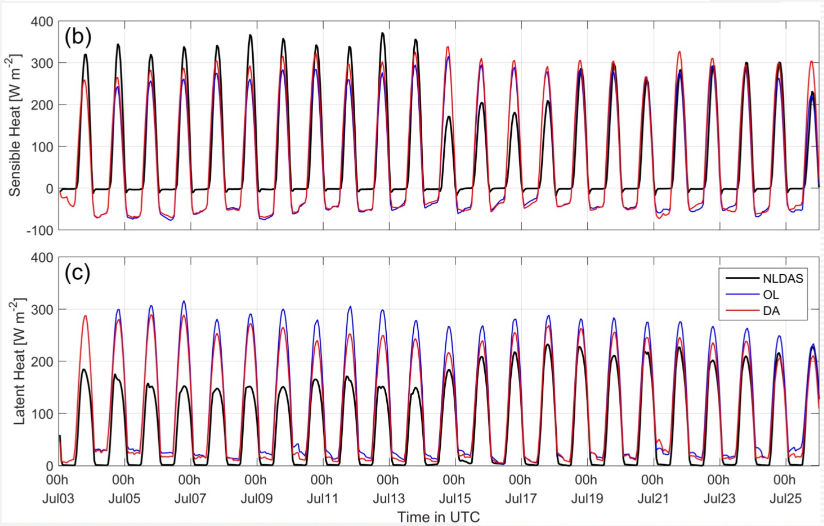




- Assimilating upscaled 6-h 20-km NCEP Stage IV precipitation in the WRF domain D01.
- Verifying the model precipitation at domain D02 against fine-scale NCEP Stage IV precipitation (Lin et al., 2017, JHM).

BIG DATA APPROACH: ASSIMILATION OF SOIL MOISTURE

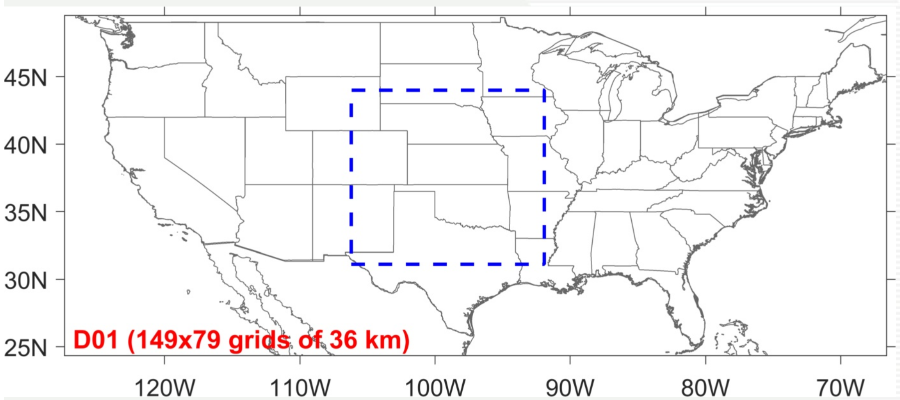




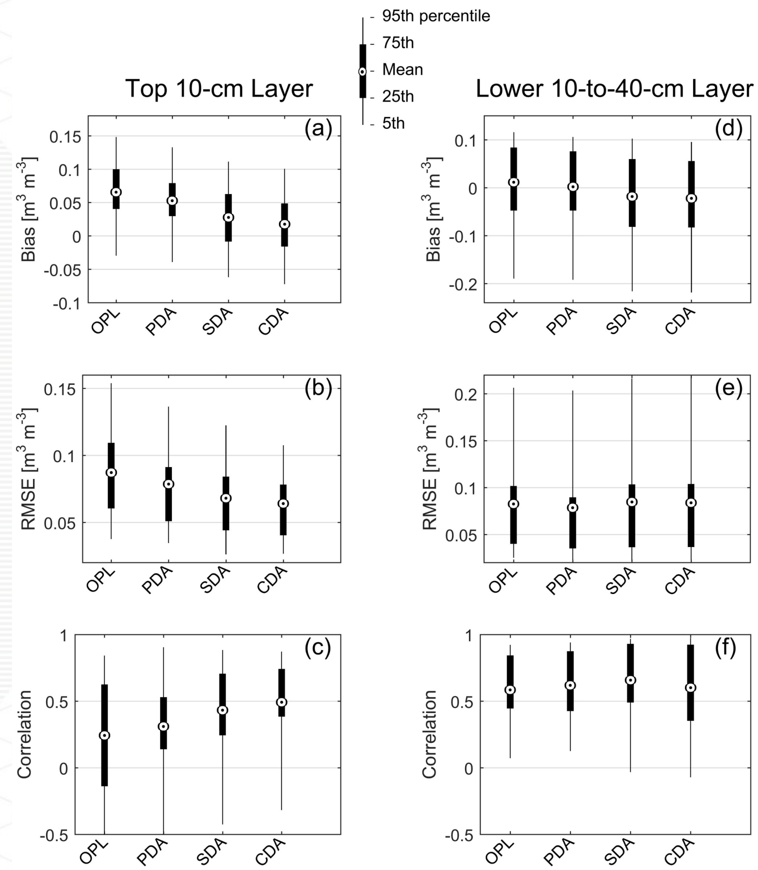
- Assimilating SMOS soil moisture into the Noah LSM domain D01 in July 2013
- Verifying the hourly gridded model soil moisture at domain D03 against the Soil Climate Analysis Network gauge data
- Verifying the heat flux simulation against NLDAS (Lin et al., 2018, WRR)

Improvement relative to Open loop (no DA)	**Top 10-cm SM**	**10-to-40-cm SM**
MAE	35%	9%
RMSE	33%	8%
Correlation	19%	25%

BIG DATA APPROACH: ASSIMILATION OF PRECIPITATION + SOIL MOISTURE



- Assimilation of TRMM 3B42 precipitation and SMOS soil moisture
- Verification of model soil moisture in the blue box against the hourly soil moisture gauge data in July 2013 (Lin et al., 2018, MWR).



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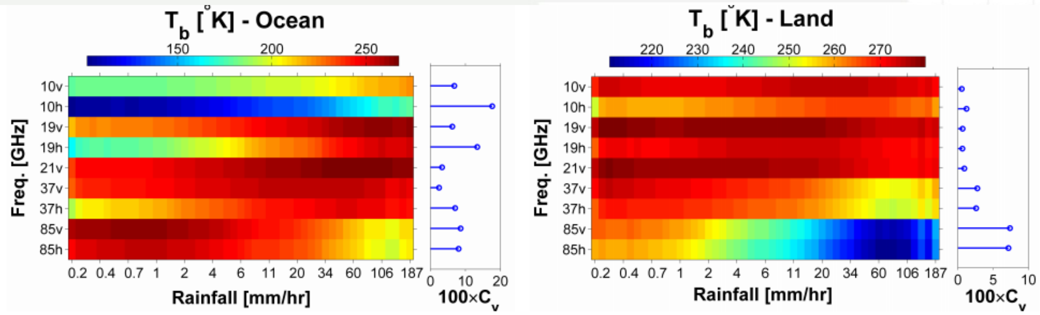
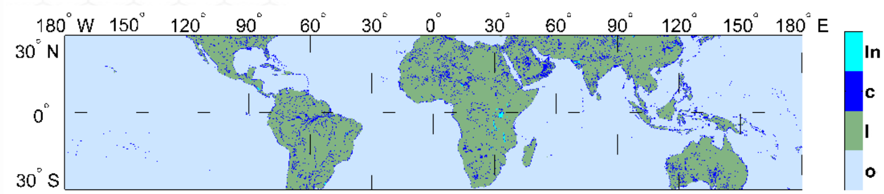
PRECIPITATION RETRIEVAL: DICTIONARY BASED SHARP ALGORITHM



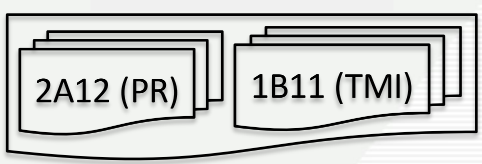
Expected values of the spectral brightness temperatures for different intervals of the surface rainfall intensity over ocean (left panel) and land (right panel)

Surface class map

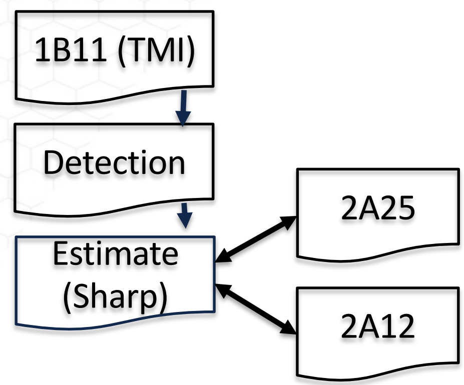


Different earth surface classes used in the current version of the ShARP, namely inland water body (In), coastal zone (c), land (l) and ocean (o). The classification is adopted based on the available data (version 7) of the PR-1C21 product, which are mapped onto a 0.05-degree regular grid

Dictionaries

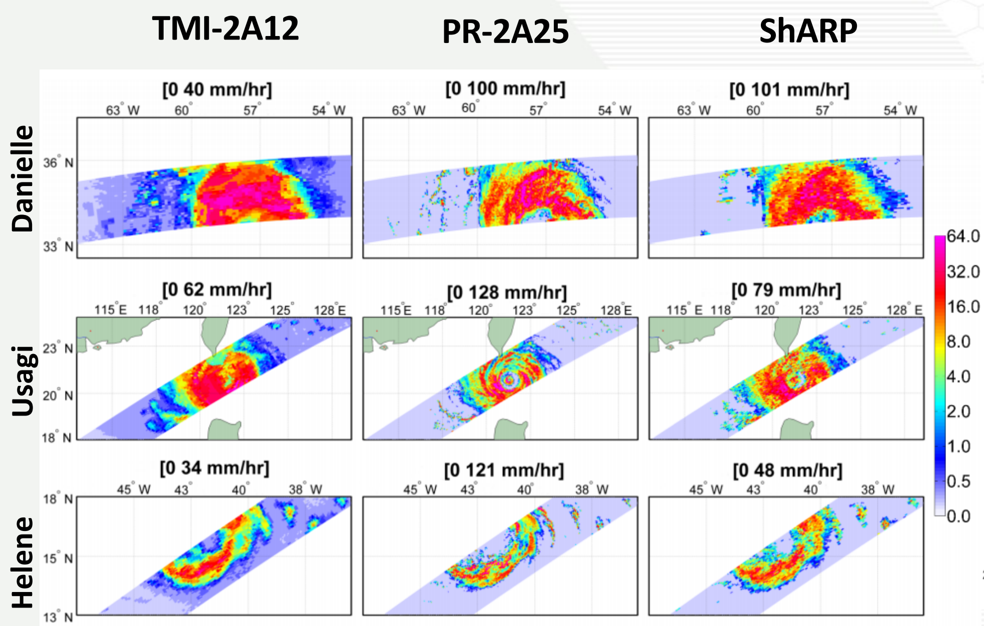


Dictionaries for 4 land classes (In, C, I, and O)

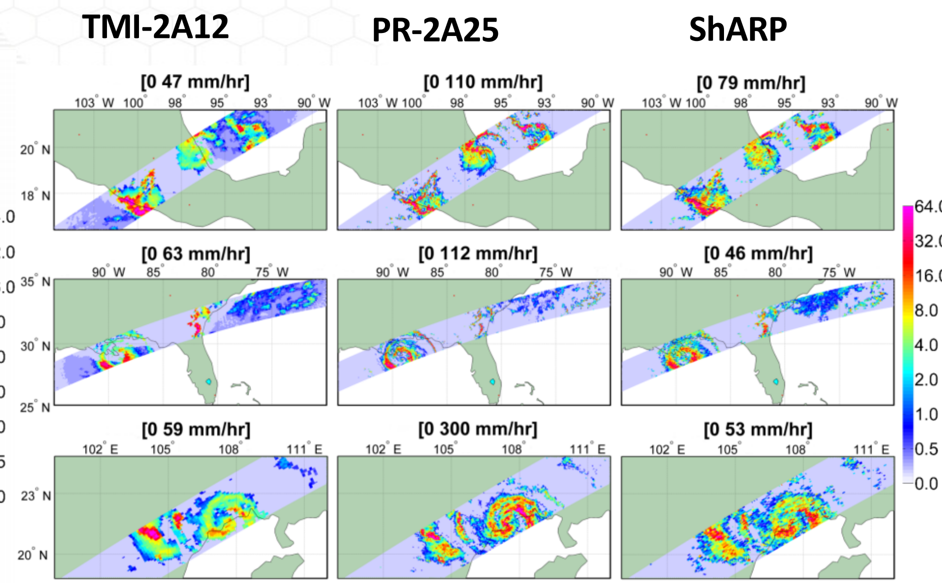


Ebtehaj A.M., Rafael L. Bras, Efi Foufoula-Georgiou (2015, IEEE)

PRECIPITATION RETRIEVAL : DICTIONARY BASED SHARP ALGORITHM



From left to right: TMI-2A12, PR-2A25 and ShARP retrievals. Top to bottom panels: hurricane Danielle in 08/29/2010 (orbit No. 72840) at 09:48 UTC; super typhoon Usagi in 09/21/2013 (orbit No. 90277) at 02:09 UTC; and tropical storm Helene in 09/15/2006 (orbit No. 50338) at 14:34 UTC.



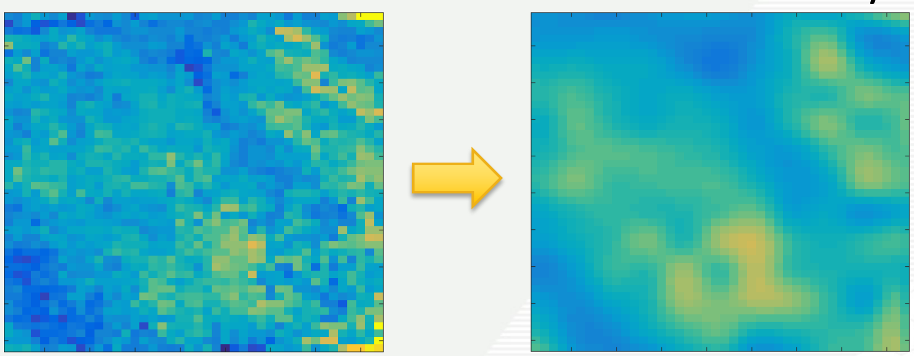
From left to right: TMI-2A12, PR-2A25 and ShARP retrievals. Top to bottom panels: tropical storm Fernand in 08/26/2013 (orbit No. 89874) at 05:30 UTC, hurricane Isaac in 28/08/2012 (orbit No. 84227) at 22:12 UTC and typhoon Kai-takin 08/17/2012 (orbit No. 84050) at 13:35 UTC.

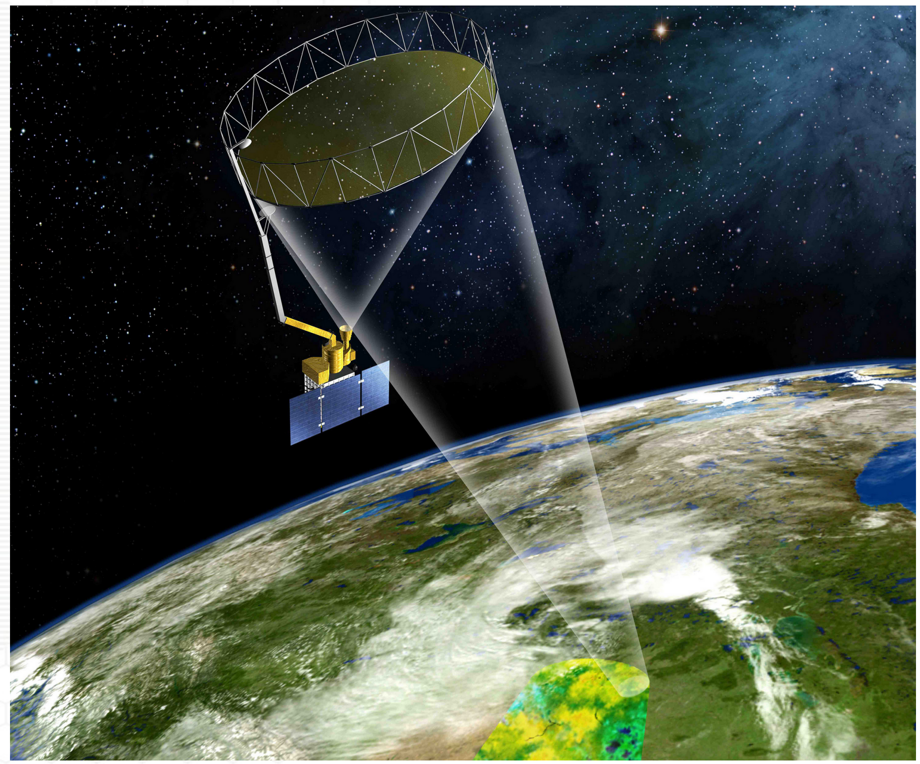
SOIL MOISTURE ACTIVE PASSIVE (SMAP)

Active Radar:	3 km
Passive Radiometer:	40 km
Combined:	10 km

Resolution loss with radar failure:

Radiometer + Radar | Radiometer Only





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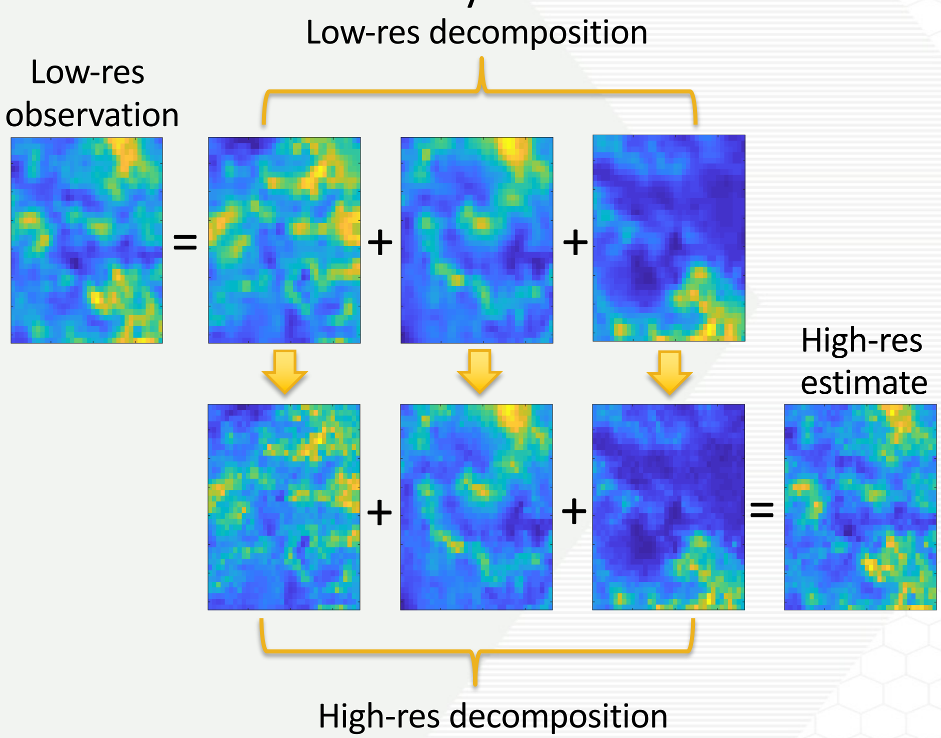
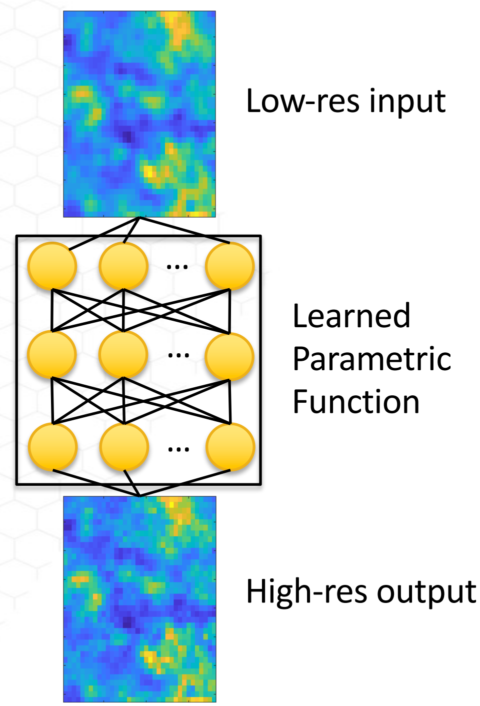
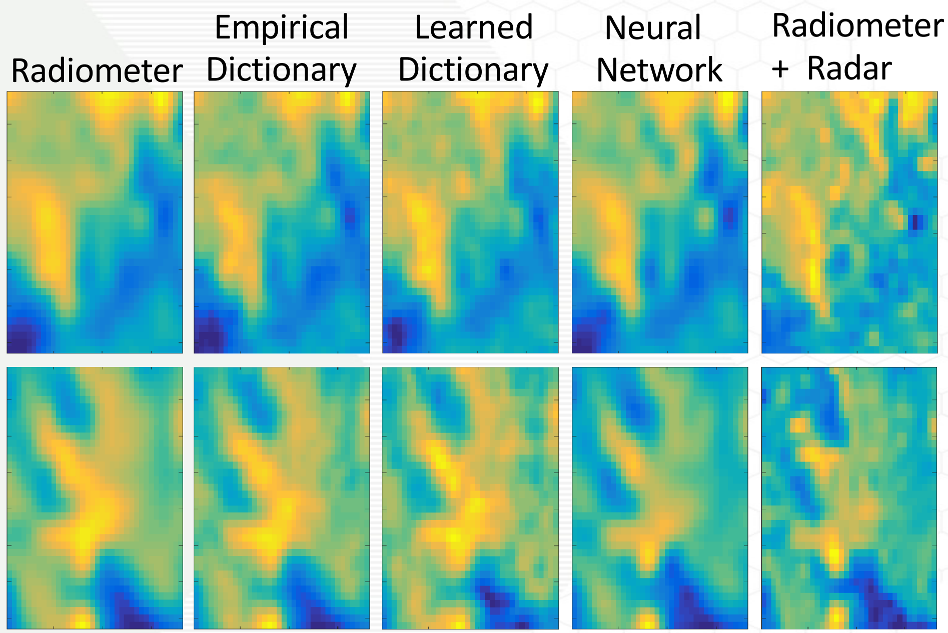
Dictionary Methods



Convolutional Neural Network

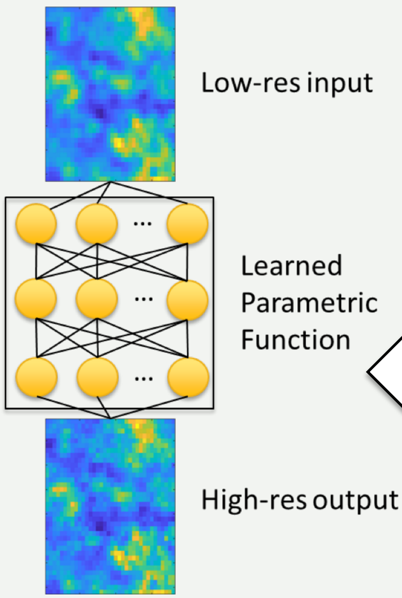


BLACK BOX SUPER-RESOLUTION OF SMAP

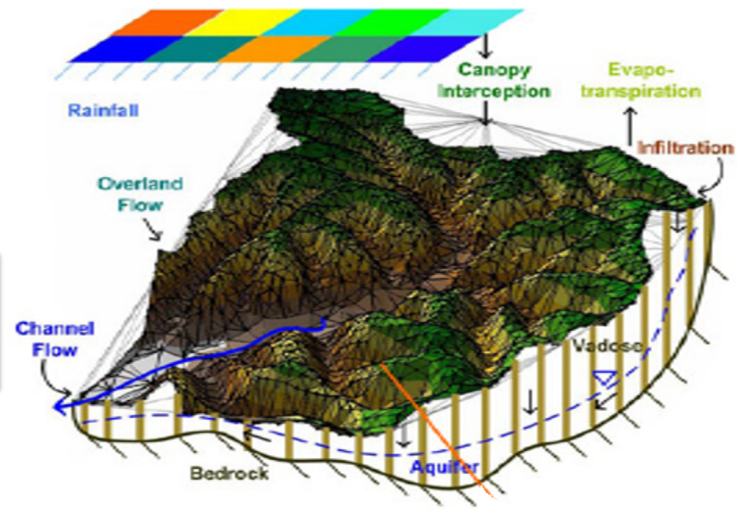


Training on all “complete” patches
Average ~1% improvement in MSE

HYBRID DATA ANALYTICS METHOD



Guide/Teach ML on how physical system behave



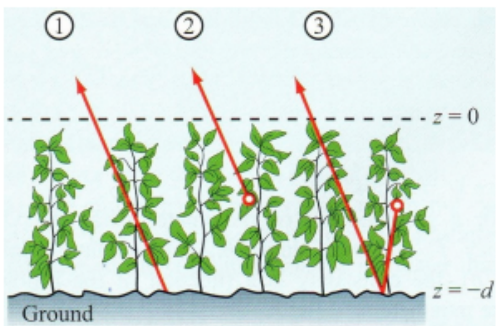
Machine learning (ML) models: Based on historical information

Physical models (e.g., tRIBS): Account of the soil's hydrological conditions, includes climatic variables to model terrestrial water balance

SOIL MOISTURE RETRIEVAL ALGORITHM

The τ-ω model at L-Band:

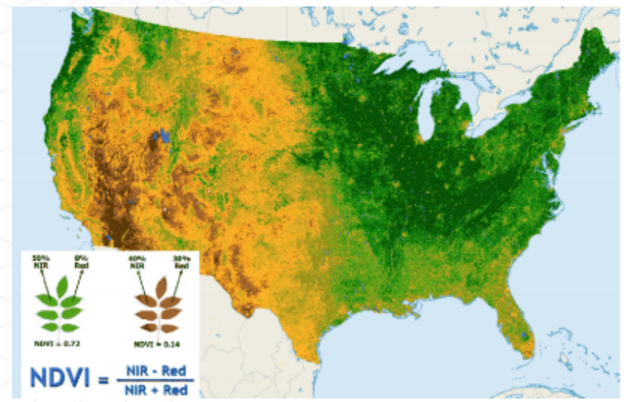
① Emission by the soil surface: $(1-r_p)\gamma T_s$
② Emission by the vegetation: $(1-\omega)(1-\gamma)T_c$
③ Emission by the vegetation followed by soil reflection: $r_p(1-\omega)(1-\gamma)\gamma T_c$



$$\mathbf{Tb_p} = (1-r_p)\gamma T_s + (1-\omega)(1-\gamma)T_c + r_p(1-\omega)(1-\gamma)\gamma T_c$$

T_s and T_c: soil and canopy temperature [K]
r_p (soil reflectivity), γ (vegetation transmissivity), ω (single scattering albedo)

- **Single channel algorithm(SCA)**
- Double channel algorithm (LS inversion)(DCA)
- **Constrained multichannel algorithm (CMCA)**



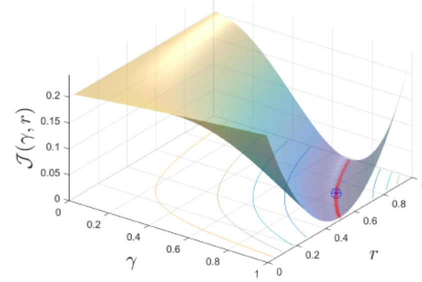
1. ω in constant and ϒ is estimated from NDVI climatology
2. Estimate r_p and infer soil moisture from Fresnel equation and a soil dielectric model

Double Channel Algorithms (DCA)

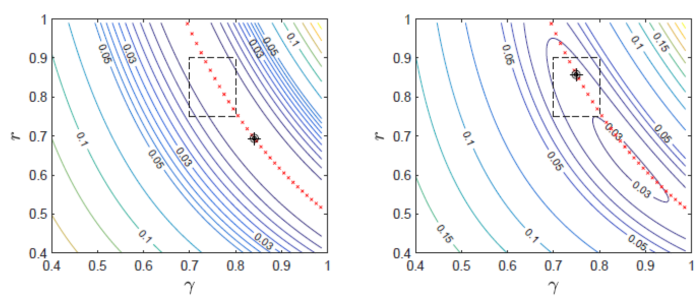
$$e_p = Tb_p/T_s = f(\theta) + \epsilon \quad \Longrightarrow \quad \theta^* = \underset{\theta}{\operatorname{argmin}} \frac{1}{2}(e_p - f(\theta))^2 + \lambda \|\theta\|_2^2 \text{ subject to } \theta_l \preceq \theta \preceq \theta_u.$$

where $\theta = (r_p, \gamma)^T$.

- The LS cost function for the $\omega = 0.05$ and $e = 0.5$.



- How about a constrained inversion?



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CONSTRAINED MULTICHANNEL RETRIEVAL ALGORITHM (CMCA): INVERSION PHYSICAL BOUNDS

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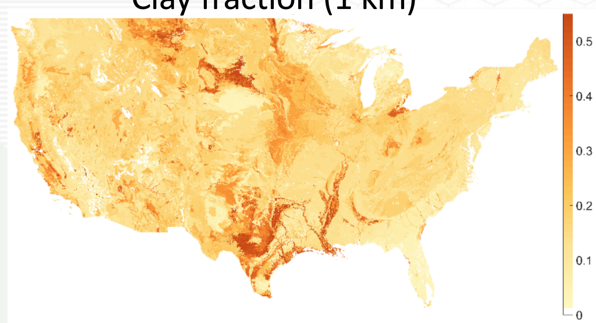
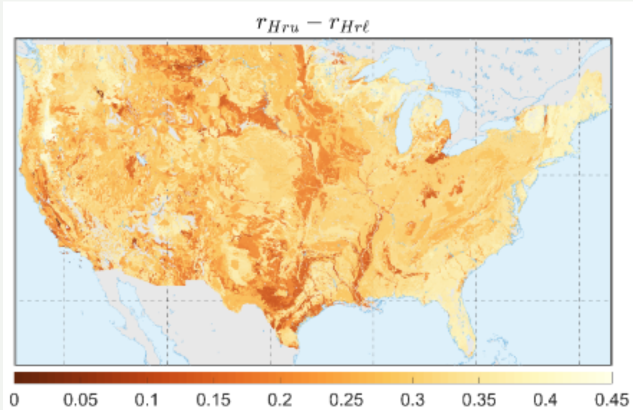
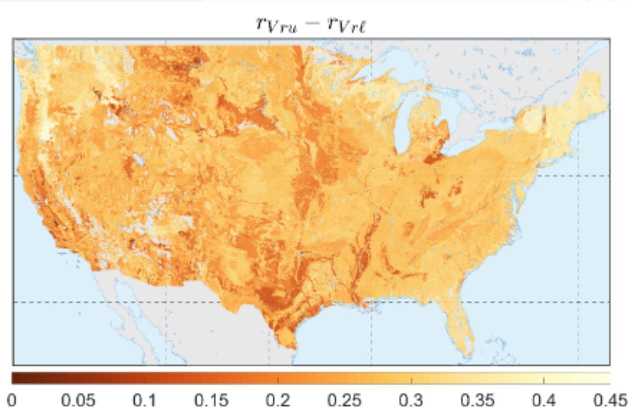
Soil texture (1 km)

Clay fraction (1 km)

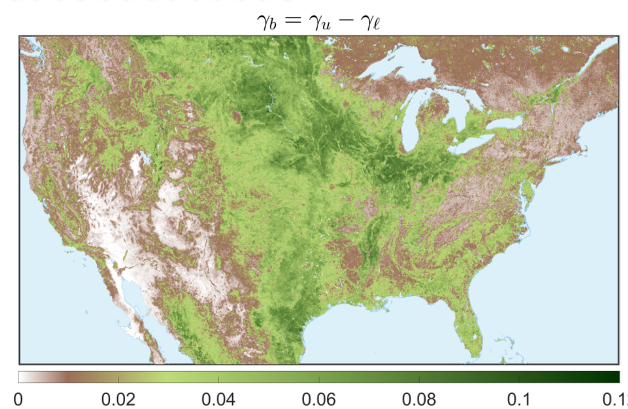


Porosity (1 km)





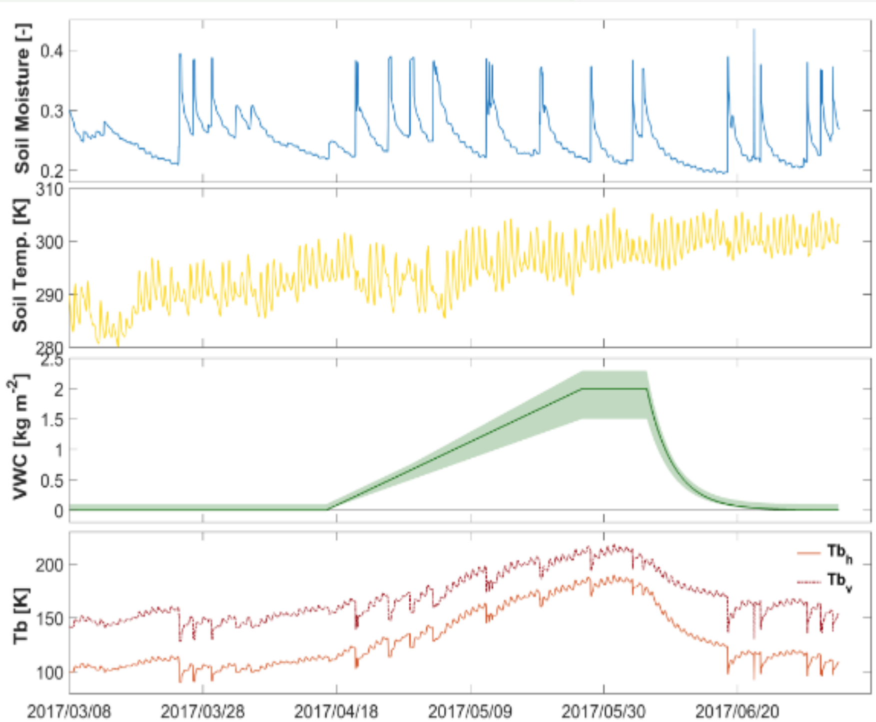
Soil reflectivity (1 km, f=1.4 GHz)



Vegetation Transmissivity (5 km)

TIME SERIES EXPERIMENT: RETRIEVAL WITH AND WITHOUT PHYSICAL CONSTRAIN

Soil Climate Analysis Network gauge station in Arkansas, US



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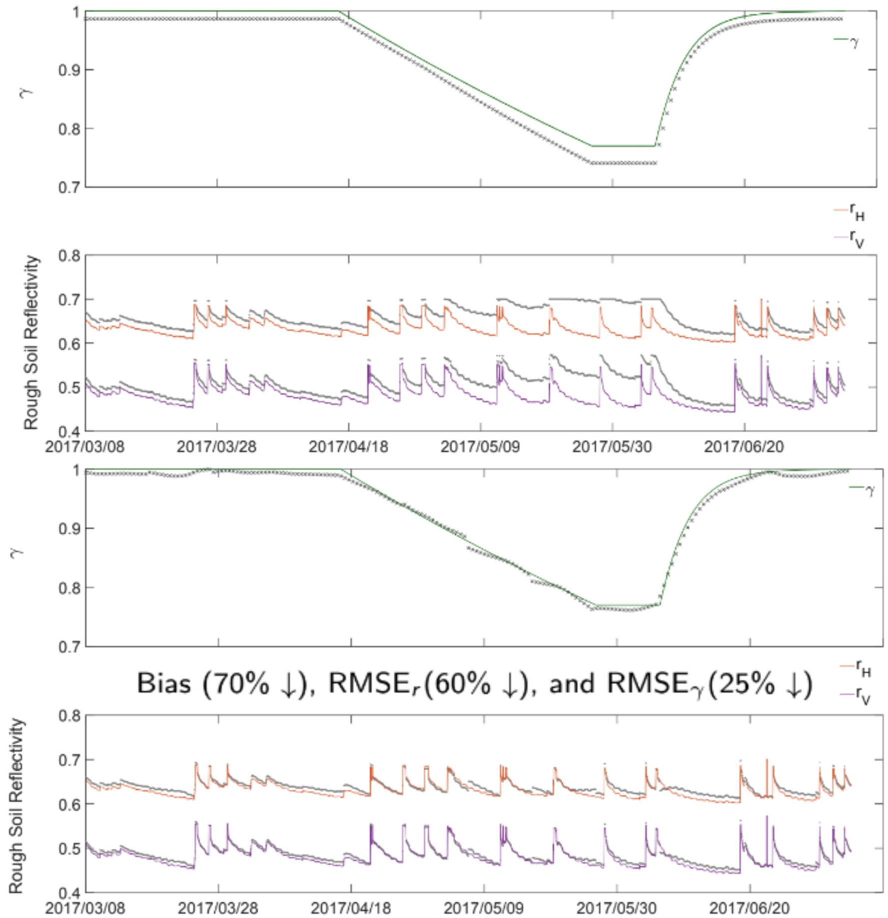
Soil moisture retrievals

→ Without physical constrain

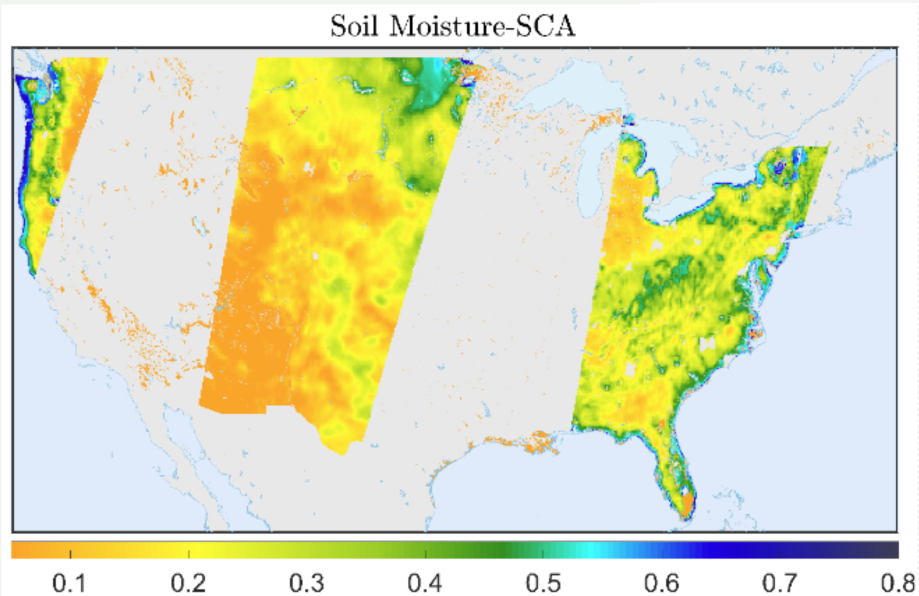
→ With physical constrain



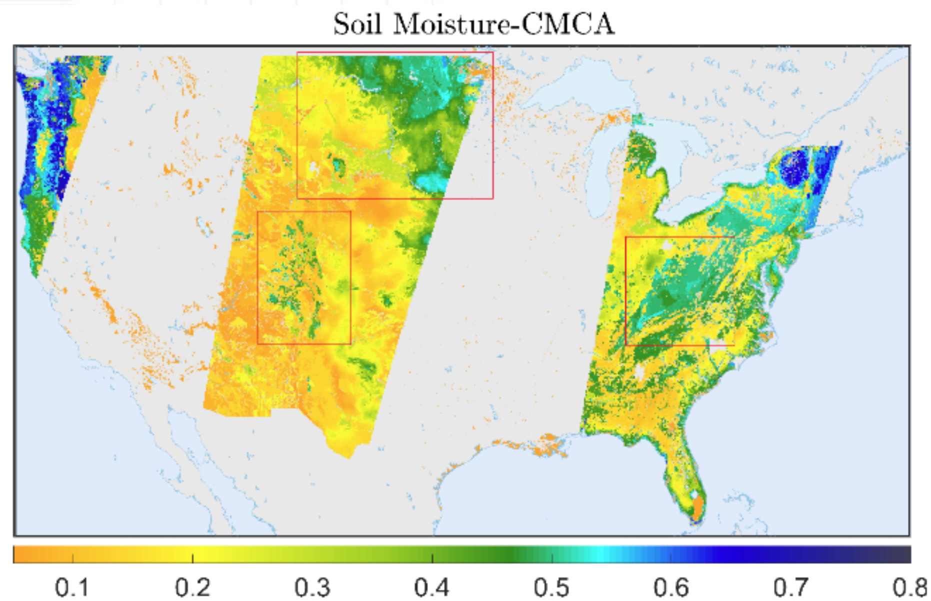
Bias (70% ↓), RMSE$_r$(60% ↓), and RMSE$_\gamma$(25% ↓)

SOIL MOISTURE RETRIEVAL: IMPLEMENTATION FOR SMAP DATA

SMAP overpass on 06/01/2016-SCA official NASA product at 9km



SMAP overpass on 06/01/2016-CMCA at 1km



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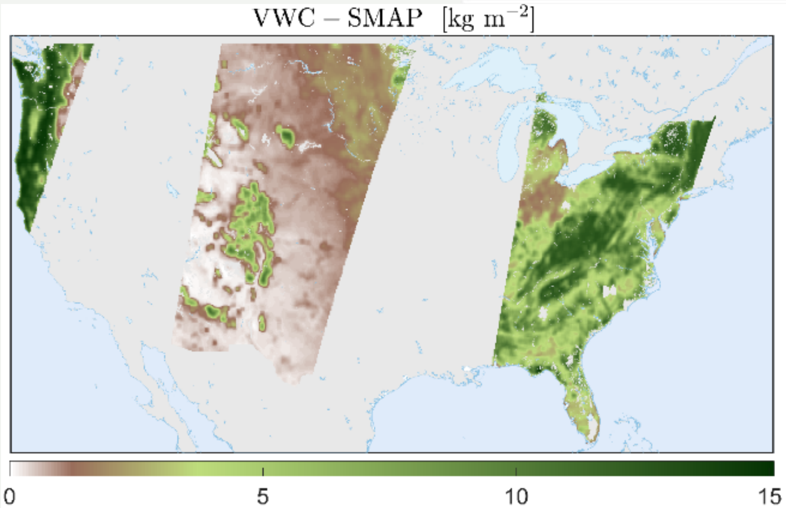
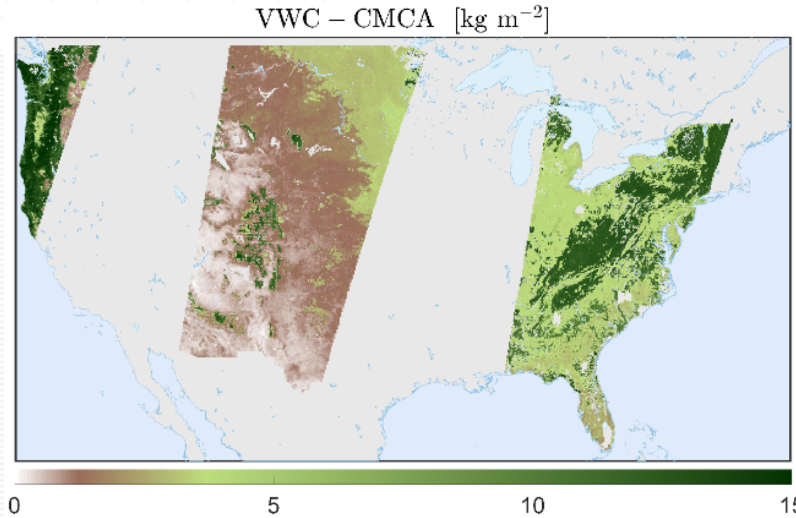
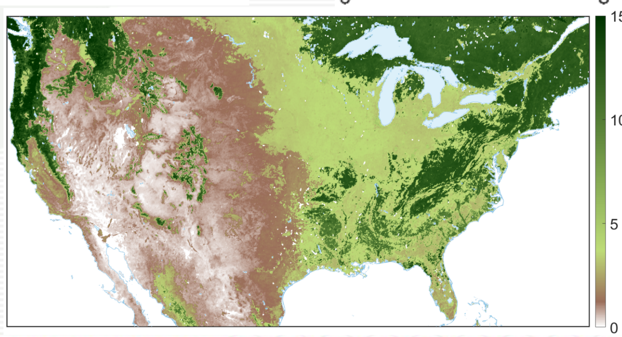
VWC RETRIEVAL: IMPLEMENTATION FOR SMAP DATA

SMAP overpass on 06/01/2016-SCA official NASA product at 9km



SMAP overpass on 06/01/2016-CMCA at 1km





MODIS (Ref.)

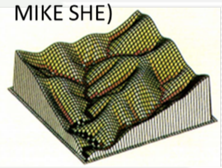
Era of Data Rich Hydrology

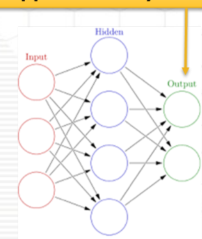
AVHRR/MODIS /Landsat

SMOS, TRMM, GPM, SMAP

Evolution of big data approach in Hydrology

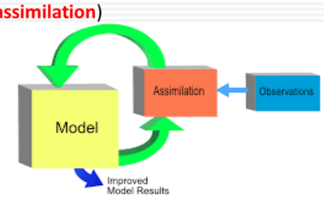
Spatially distributed physically based models (e.g., tRIBS, MIKE SHE)



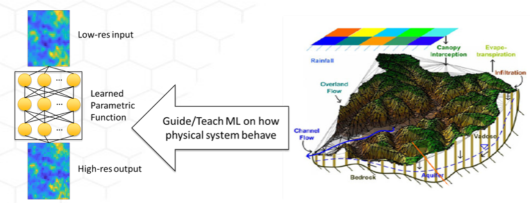


Machine/deep learning (Super resolution for downscaling)

Reliable estimation of geospatial data, model forcing, parameter estimation, state estimation (**data assimilation**)



Hybrid Analytics (Combining machine learning with physically based models)



Thank You!